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Supervised Machine Learning based Predictive Modelling of Student Academic Performance in E-learning during COVID-19 Pandemic

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The COVID-19 pandemic has drastically altered educational landscapes worldwide, prompting the need for effective student performance prediction models in e-learning environments. Traditional methods of monitoring and supporting student progress became less effective in virtual environments, where variables such as student engagement, access to technology, and adaptability to online platforms played a crucial role. Educational institutions lacked robust, data-driven tools to predict academic outcomes and identify at-risk students in real time. This limitation hindered timely interventions and exacerbated learning disparities. Hence, this paper proposes a supervised machine-learning approach to enhance the prediction of student academic performance during the pandemic. Using two benchmark datasets comprising student demographics, use of e-learning tools, sleeping habits, psychological state, and academic scores, multiple supervised ML models, including Multi-Layer Perceptron (MLP), Random Forest (RF), Support Vector Machine (SVM), and XGBoost (XGB) were trained and evaluated for performance prediction. This paper also highlights the importance of feature selection, emphasizing factors such as attendance, online participation, and prior academic records. Evaluation metrics such as accuracy, f-score, precision, and recall were used to assess model performance, with RF achieving the highest accuracy of 87.1%. The findings provide actionable insights for educators and institutions to identify at-risk students and devise targeted interventions. By leveraging predictive analytics, this paper contributes to the development of more adaptive and student-centered e-learning systems, fostering academic resilience during

unprecedented disruptions.
Keywords: Machine Learning, Educational Data Mining, E-learning, Supervised Classification, Students Academic Performance.

1. Introduction

The global outbreak of COVID-19 has had a profound impact on individuals' daily schedules and work methodologies. Governments throughout the world have imposed strict curfews and quarantines to stem the spread of the COVID-19 epidemic. Global educational systems have been hit hard by the effects of the Coronavirus epidemic in the past several years, with many schools and colleges having to close their doors permanently. Many governments worldwide have implemented temporary closures of colleges and universities to manage the pandemic [1]. The majority of educational institutions have implemented emergency remote learning using online learning platforms instead of traditional classroom instruction as a result of the unpredictability of the pandemic's duration. Courses that were once only offered in person are quickly moving online so that students may complete their education without having to wait as long to graduate, go on to graduate school or get a job. Getting an education in the traditional sense is a great way to learn about the world and its people. The capacity to distinguish between good and wrong is also bestowed upon the human mind by this process of education. People who are engaged in learning receive training when an educator imparts knowledge, abilities, and facts to them [2].

Data mining is the systematic extraction of valuable insights from specific databases. Discovering correlations between parameters and extracting hidden patterns in massive amounts of data are both made easier with its guidance. Many academics nowadays use Data Mining to address practical issues in fields including marketing, telecommunications, healthcare, medicine, industry, and customer relationship management [3]. More and more, data mining has found its way into the classroom as of late [4]. In today's universities, the academic success of each student is crucial. For the simple reason that a school's track record of student achievement is one indicator of its quality [5]. Forecasting how well students will do in school is a major issue for education administrators and other professionals in the sector. If the prediction is accurate, it might alert at-risk pupils promptly about their impending academic failure [6]. Predicting student performance was enough before COVID-19 and the global shutdown of educational institutions. Since many colleges employ e-learning technologies due to the pandemic, characteristics that better reflect students' learning environments must be considered. The psychological impact of the lockdown was evaluated through the use of a survey that was administered to undergraduate students of varying ages and majors. Discovering patterns in educational data via the use of machine learning (ML) techniques is the objective of Educational Data Mining. This is done to predict how well children will perform in school. One possible use case for this is building a prediction model [7].

Some of the data analysis and processing methods used in data mining include association rules, clustering or classification, and sequence analysis [8-9]. Using a classification technique, we may label every single object in a collection. Every example in the dataset needs a precise prediction of the target class, therefore this is done [10]. There are several techniques used in educational data mining such as Decision Trees (DT), Naïve Bayes (NB), Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Artificial Neural Networks (ANN) and others. As a basic stance in an informative setting, predicting and analysing student execution is essential. The educational execution of students is a crucial component in their future development. The academic success of a student is dependent on more than just one factor; it is also strongly influenced by factors such as socioeconomic status, psychological makeup, and other contextual factors. The main objectives of this paper are:

1. Designed Supervised ML based framework to predict whether the student performance satisfactory during the COVID-19 pandemic.
2. Generated a dataset by conducting an online survey using a structured questionnaire among undergraduate students.
3. Tested classification algorithms by assessments made experimentally in relation to the parameters of the confusion matrix.
4. Created a predictive model to forecast the probability of students embracing e-learning and its resources in the decades following the current pandemic.

The outline of the paper is presented as follows. Section II provides a comprehensive review of the pertinent literature. The content and processes are defined in Section III. Section IV explores the outcomes and their interpretation of the experiments. Finally, the study concludes in Section VI by presenting the implications that have been deduced from the obtained data.

2. Related Work

2.1 Existing Methods

The existing literature related to prediction model of student performance is discussed in this section. The predictive model of student performance combines various statistical analyses of time series to gather students learning behaviors and quantify the relationship between many features to clarify how numerous factors impact student's performance [1]. Regularized ensemble learning approaches analyse student performance data and draw reliable inferences [2]. Different ML approaches are used to evaluate student computer science skills [3]. By identifying at-risk learners early, the predictive approach might transform education [4]. A emerging method for predicting and categorizing online learning flexibility among those who might struggle owing to demographic and academic factors [5]. In terms of predicting student happiness, the decision tree classifier was more effective than the naïve Bayes. Among other factors, the presence of a feeling of community during online learning was the most influential factor in determining satisfaction [7]. A combination of ANN and RF model used to forecast how students would feel and how satisfied they would be with the course [8]. A wider context applied since they demonstrate that retention prediction models trained on one institution can achieve respectable results when applied to a different institution [9]. Supervised ML techniques are used to investigate probationary college students' poor academic performance [10].

The utilization of two machine learning techniques, specifically SVM and KNN, enables the prediction of the rate of churn for EdTech courses based on student response obtained from the course end assessment [11]. An investigation on the effects of distance learning on student well-being within the COVID-19 pandemic in Kenya, with particular attention to the moderating role of student preferences in this relationship [12]. A descriptive-analytical approach was employed to analyse the viewpoints of the sample about the quality assessment of distance learning courses. The objective was to determine and assess the extent to which requirements for distance learning courses have been met [13]. During this pandemic circumstance, university students in Sri Lanka used e-learning tools to research and predict how institutions will adapt to e-learning [14]. The COVID-19 epidemic and its aftermath may predict student academic achievement [15]. Comparing the new Inception approach with the Google algorithm improved distance education COVID-19 exam prediction [16]. Examining and contrasting six ML models based on Thailand's educational curriculum for early performance prediction of students [17]. Throughout the epidemic, a complete sentiment analysis and emotion mining (EM) was carried out on tweets in Arabic that were connected to distant learning [18]. ML model proposed for predicting enhance learning success, which includes extra steps for pre-training with fine-tuning, and builds a mechanism for generating adapted feedback [19]. The level of student pleasure mentioned during a tutoring discussion is a significant measure of its effectiveness [20].

Researchers looked at how to use ML model to gauge students' happiness with their online courses in a wireless network setting [21]. The hypothesis of psychological contracts and their potential connection to students' happiness with online education was investigated [22]. The main learning tool and the primary indicators for undergraduate students' satisfaction with ERL are these two platforms [23]. Examining the relationship between student happiness and engagement in e-classroom study activities and performance is evaluated [24]. An effective method for sentiment categorization that followed the tenets of deep learning (DL) and ensemble learning showed strong prediction abilities in evaluations of massive open online courses (MOOC) [25]. Using sentiment analysis on Twitter, one of the most prominent social media platforms, the community has come to embrace remote learning as a safety measure [26]. Predictive algorithms that are appropriate for early dropout prediction systems at universities in online learning are intended to be presented using the learner's statistical information and computed data, furthermore, the data that is documented inside the system for learning management [27]. The program used ANN to analyse data from students at the University of Tabuk to determine what characteristics contribute to their level of satisfaction with online learning [28]. Analysing data collected over successive years allowed us to anticipate student participation in the early stages of a virtual learning environment course [29]. Research into the potential of automated categorization for the semantic content of evaluations of massive open online courses (MOOCs) aimed at identifying elements that, according to learners, might indicate their level of satisfaction with the courses [30]. A Deep Neural Network–based approach was suggested for predicting students' grades [31]. An approach that utilizes data mining techniques to forecast how well computer science students would do in school [32]. The creation and use of graphical models, such as correlation graphs and correlation chains, that may be used to visualize the prediction potential of data and highlight the pseudo-transitivity of a dataset [33]. A feature Perturbation (FP) module was included to improve the model's stability and resilience by enabling it to adapt to various intricate industrial scenarios [34].

2.2 Limitations in Existing Research

The most renowned research on forecasting student's performance achievement during a pandemic emphasizes certain areas of strength and regions of deficiency. The evaluations were deemed ineffective due to their lack of specificity, failure to prioritize student outcomes as a metric of student achievement, issues with quality, and limited accessibility through publicly searchable platforms. This work aims to create a prediction algorithm that analyses students' internet activity during the COVID-19 epidemic to forecast their academic performance, utilizing recently gathered statistical indicators.

3.Proposed Methodology

This section presents a conceptual process of this research, which utilizes selected classification approaches. The procedure for developing a predictive model to assess student performance satisfaction throughout the epidemic using a supervised machine learning model appears in Figure 1.

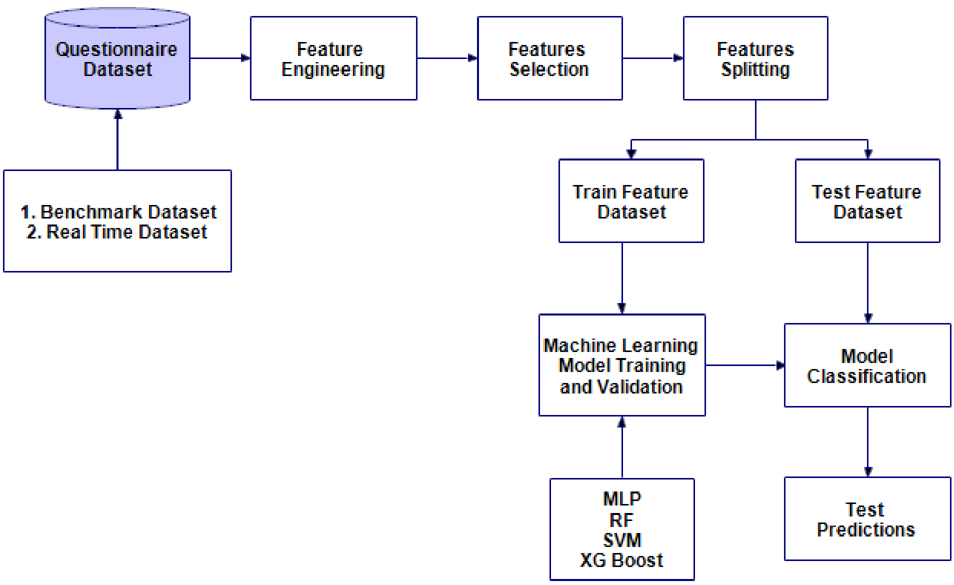

Fig. 1. Framework for Prediction of Student's Academic Performance

3.1 Questionnaire Datasets

A. Benchmark Questionnaire Dataset [15]

The researchers utilized a widely accepted benchmark collection of questionnaires [15]. A Likert scale survey, based on a Google form, was used to poll undergraduates from several colleges across India. On top of that, students were issued to fill out the form with similar information mentioned in table 1. Later on, it was incorporated into the dataset that was first collected. Of the thirty columns that make up the feature set, twenty-two of them are used to represent replies to surveys using the Likert scale, the binary data and category variables. The poll started in March 2021, on a Likert-style five-point scale ranging from 0 to 4. During this period, the vast majority of students depended on different online learning tools to accomplish their academic goals. The survey consisted of five sections, each of which focused on students' inquiries about their use of online resources for educational purposes and the effect of this consumption on their academic achievement. An important factor to highlight is the significance of characteristics that fairly depict the educational environment in which modern students find themselves. Table 1 contains labels for the target grade point average.

Table 1. Output Attributes Using Label Encoding

Output Class	**GPA Score**
Class-1	+90
Class-2	80-89
Class-3	70-79
Class-4	60-69

B. Real Time Collected Dataset

Due to the prevalence of student surveys in recent academic research, this study includes surveys from universities in the Amravati City area. It calls for a low-cost method of data gathering and analysis that is both efficient and quick, as well as one that reduces administrative error. In online surveys, the absence of constraints such as digitally produced followers and specific preferences is observed, the pool of potential learners is larger. Furthermore, in this urgent scenario, the most vital component is to obtain the necessary and accurate data on time. Collecting the necessary data was the backbone of the study. To achieve this goal, a Google Forms questionnaire was created and sent via email and social media to student organizations and forums at eighteen different institutions.

Three types of questions make up the questionnaire. Gathering the respondent's details is the first step. Part two entails collecting information on the tools and resources utilized for online education, part three concerns the respondent's language skills as they relate to the features offered by online learning platforms, and part four gathers data regarding e-learning's practical applications. Data was saved in a comma-separated values format from a total of 500 questionnaire replies. Tables 2, 3, and 4 below outline the components of the dataset, which include both independent and dependent variables.

Table 2. Dataset Input Parameters

Name of Attributes	**No of Values**	**Description**
Gender	2	Male, Female
Year of Study	4	First, Second, Third, Fourth
Age Group	3	18-24, 25-30, 30+
UG Percentage	5	+90, 80-89, 70-79, 60-69, Below 60
Residence	4	Remote area, Village, City, Metro city
Parents Education	4	Below 10th, 12th, UG, PG
Use of Digital tools for Parents	3	Highly expert, Familiar, Not Familiar
network issue while learning online	2	Yes, No

Table 3. Dataset Input Parameters with Questions

Attributes	Questions	Descriptions
Use of Digital Tools	Q1	How often do you use each of these digital tools?
	Q2	How often do you use the various digital learning resources?
	Q3	How often do you use the digital tools (mobile, i-pad, laptop) while studying?
	Q4	Using the digital tools for e-learning causes me to become distracted and unable to focus?
	Q5	Am I proficient in the necessary technologies or applications?
Sleeping Habits	Q1	How much times that student goes to bed and wakeup?
	Q2	Extended usage of digital learning tools has impacted the sleeping patterns?
	Q3	Online learning's constant screen time is stressful?
Social Interaction	Q1	Digitization causes social distance?
	Q2	Long-term usage of digital tools isolates students.
	Q3	University study improves students' social skills?
	Q4	Laziness and lethargy result from being home?
	Q5	Family members help in learning online?
Psychological State	Q1	Extended usage of e-learning technologies can cause boredom, anxiety, and stress?
	Q2	The psychological aspect is crucial to educational performance?
	Q3	An embarrassment and a frustration for some students is that they cannot afford to purchase all of the essential digital tools?
	Q4	Online learning is detrimental socially and mentally; hence student don't encourage it?
	Q5	COVID-19 lockdowns, closures, and quarantines generated tension, frustration, and sadness?
	Q6	I enjoyed attending lectures and tutorials?
	Q7	I was satisfied with online learning course?
	Q8	Were parents satisfied with online learning?
Academic Performance	Q1	Intense e-learning tasks caused confusion, dissatisfaction, and poor performance?
	Q2	Academic performance improves with face-to-face engagement?
	Q3	Online quizzes and examinations made me uneasy?

Table 4. Dataset Output Parameters

Grade	GPA Grade Scale
Grade-4 (C)	60-69
Grade-3 (B)	70-79
Grade-2 (A)	80-89
Grade-1 (A+)	+90

3.2Feature Engineering, Selection and Splitting

Feature engineering refers to a collection of approaches that a system may employ to detect and categorize characteristics. Included in the survey results are multiple feature columns with Likert scale replies; one column contains only binary responses; and the remaining feature columns offer responses depending on a variety of category values, including the target GPA. Feature encoding is a crucial process in preparing categorical and textual input for machine learning models. It is dependent on the qualities of the data as well as the requirements of the particular algorithm that is being used to determine which encoding approach should be chosen. Every encoding strategy offers a distinct method of mathematically describing categorical data, which can have a substantial influence on the

performance of ML model. Label encoding is a common method for transforming data into a numerical or binary format that machines can understand and interpret. To make the data machine-readable, labels are encoded each output label data point. A distinct number is assigned by label encoding to every category in a categorical variable. Usually, this approach is applied when there is an ordinal association among the categories.
When n categories $\{c1,c2,...,cn\}$ are present in an output categorical variable X, label encoding assigns an integer $i \in \{1,2,\ldots,n\}$ to each category ci.

$$\text{Label}(ci) = i$$

Following that, a one-hot encoding is performed on every input category characteristic. When it comes to representing categorical characteristics as binary vectors, one-hot encoding is an approach that is frequently utilized. There is one dimension for each potential category, and each category is represented as a vector with one dimension. The location that corresponds to the category is set to 1, while all other positions are set to 0.
Given a input categorical variable X with n categories $\{c1,c2,\ldots,cn\}$, the one-hot encoded vector ei for category ci is:

$$ei = [0,0,\ldots,1,\ldots,0]$$

Where:

- The vector ei $\in R^n$ has all elements as 0 except at the position corresponding to the category ci.

The feature data is cleaned up by removing any NaN values. To decrease variance in the test dataset, retain only one feature if its association with goal value is weak or if two characteristics are highly associated. A disproportionate percentage of people with lower incomes are on list of target labels. An asymmetrical sample may give rise to a biased model. With the use of the Synthetic Minority Oversampling Technique (SMOTE), it was demonstrated that the samples obtained from the minority class were more representative of the majority class. In the process of training machine learning models, unbalanced datasets might result in models that favour the dominant class and then cause the minority class to behave poorly. This problem is addressed by SMOTE, which generates synthetic samples for the minority class to adequately balance the dataset.

Algorithm 1: Implementation of SMOTE

Step 1: Determine the k-nearest neighbours of each minority class sample x.
Step 2: Randomly select one of the neighbours $x_{neighbour}$.
Step 3: Generate a synthetic sample:

$$x_{synthetic} = x + \lambda \times (x_{neighbour} - x),\ \lambda \in [0,1]$$

Step 4: Repeat this process until the desired number of synthetic samples is created.

The data frame was subjected to many data mining algorithms following its partitioning into a test and train set. For the most accurate classification model, divide the feature data into a 30% test set and a 70% train set.

3.3Machine Learning Modelling (Training, Validation and Classification)

In the subsequent stage of the development of the prediction model, the process of feature extraction, model training, and evaluating its performance will also be carried out. Constructing the model was accomplished through the utilization of supervised classification techniques, with the training dataset from the previous stage being utilized. Since the beginning of the data mining phase, the situation has become far more serious. The parameters of the classifier are optimized by the use of a technique known as 10-fold cross-validation. On the other hand, k-fold cross-validation utlized to lessen the impact of experimental bias and determine which fold selection is the most appropriate for the prediction framework. The testing data was furthermore utilized to evaluate a model that has the potential to forecast pupils' academic performance. Now that the data has been obtained, it has to be analysed and then incorporated into a knowledge base. The project utilizes classifiers from the Multi-Layer Perceptron Neural Network (MLP-NN), Random Forest (RF), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGB) families.

A. Multi-Layer Perceptron Neural Network (MLP-NN)

A feed-forward multi-layered artificial neural network, it takes a set of inputs and produces a set of outputs. MLP-NN is constructed by connecting the input and output layers of a directed graph with many layers of input nodes. One way to train an MLP-NN network is by backpropagation. Figure 2 below shows an illustration of a neural network model.

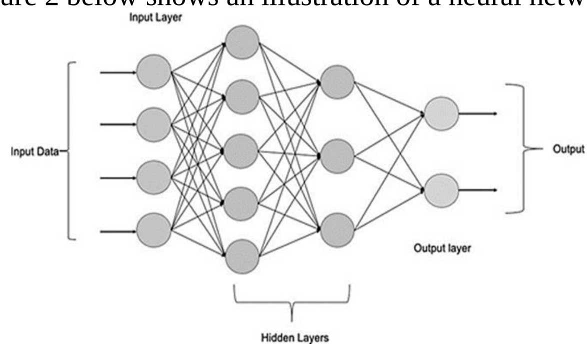

Fig. 2. Layer representation of MLP-NN

An input, one or more hidden, and an output layer are the components that make up a model. Each layer is completely linked to the one that comes after it, and the weights of the network are adjusted through the process of backpropagation during training.

Given a labeled dataset $Q_{D,}$

$$Q_D = \{(f1,t1),(f2,t2),\ldots,(fn,tn)\}$$

Where, *fi* denotes to the feature vector of the *i*-th sample, *ti* denotes to the label that corresponds to the classification

For each input sample *xi*:

Compute the Activation of the Hidden Layers, For each neuron in a hidden layer:

$$z_j = \sum_{i=1}^{n} w_{ij} \cdot x_i + b_j$$

where, *wij* are the weights connecting the input neurons to the hidden neurons, *bj* is the bias term.

Algorithm 2: Implementation of MLP-NN
Step 1: Define the Problem - Determine input features, labels, and output format *Step 2:* Initialize the Network - Specify the input, hidden, and output layer. *Step 3:* Initialize weights and biases - Initialize modest weights and biases at random. *Step 4:* Feedforward Propagation - Compute activations layer by layer from input to output. *Step 5:* Calculate Loss - Measure the error using a suitable loss function. *Step 6:* Backpropagation - Compute gradients and update weights using gradient descent. *Step 7:* Model Evaluation - Validate the model and assess its performance. *Step 8:* Hyperparameter Tuning - Optimize the architecture and training process.

B. Random Forest (RF)

It is a technique used to enhance the accuracy of predictions and mitigate overfitting. It achieves this by calculating the mean outcome from several decision tree classification methods, each trained on a distinct subset of the dataset. A random forest takes an average of predictions made by several decision trees rather than relying on a single tree to make predictions. Overfitting is less likely to occur when there are more trees in the forest, leading to more trustworthy outcomes. The Random Forest approach in action in the figure 3 below.

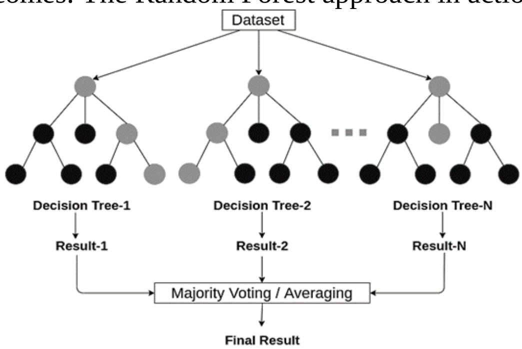

Fig. 3. Working of RF algorithm

Algorithm 3: Implementation of RF
Step 1: Bootstrap Sampling - Generate multiple bootstrapped datasets from the original dataset. *Step 2:* Build Multiple Decision Trees: To find the optimal split, randomly choose a subset of characteristics at each node in each tree. Grow the trees fully without pruning. Repeat until the stopping criterion is met. *Step 3:* Voting/Averaging: For classification, the majority vote determines the final class label. *Step 4:* Out-of-Bag Error Estimation: Optionally estimate error using out-of-bag samples. *Step 5:* Model Evaluation: Use relevant metrics to evaluate the performance. *Step 6:* Feature Importance Analysis: Optionally, extract feature importance scores.

C. Support Vector Machine (SVM)

SVM model uses a multidimensional hyperplane to project the different categories. By iteratively generating the hyperplane, SVM aims to minimize the error to its maximum potential. Finding a maximum marginal hyperplane (MMH) is the end objective of SVMs, which classify datasets into categories. The method works by finding the hyperplane inside a multi-dimensional space that best divides data points into different classifications. The goal is to maximize the distance between the closest data points—also known as support vectors—of various classes. The linear hyperplane equation can be expressed as:

$$w^T x + b = 0$$

Determine the optimal hyperplane *w.x + b = 0* with the highest margin between the two classes and the lowest classification error.

Use optimization techniques such as Sequential Minimal Optimization (SMO) or gradient descent to solve for the Lagrange multipliers αi. Once αi values are obtained, calculate the weights *w* and bias *b*:

$$w = \sum_{i=1}^{n} \alpha_i y_i x_i$$

$$b = y_k - \sum_{i=1}^{n} \alpha_i y_i K(x_i, x_k)$$

Where *xk* is any support vector. The decision function for classifying a new input *x* is:

$$f(x) = \text{sign}(w \cdot x + b) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\right)$$

Algorithm 4: Implementation of SVM
Step 1: Problem Setup - Define the dataset with input features and labels.
Step 2: Kernel Selection - Choose an appropriate kernel function for non-linear data.
Step 3: Optimization Objective - Maximize the margin between the classes.
Step 4: Mathematical Formulation - Express the problem using Lagrange multipliers.
Step 5: Solve the Optimization Problem - Use techniques like SMO to compute the optimal αi.
Step 6: Decision Function - Classify new data points based on the decision boundary.
Step 7: Model Evaluation - Utilize suitable metrics to assess the model's performance.

D. XG Boost (XGB)

XGBoost has emerged as a prominent machine learning methodology due to its remarkable scalability and the capability to surpass contemporary techniques in domains like as classification and regression. XGBoost classifier fine-tuned for scalability and speed, making it an ideal choice for training machine-learning models. Through the use of ensemble learning, many weak models predictions are combined into one single, more solid prediction and its implementation flow given in figure 4.

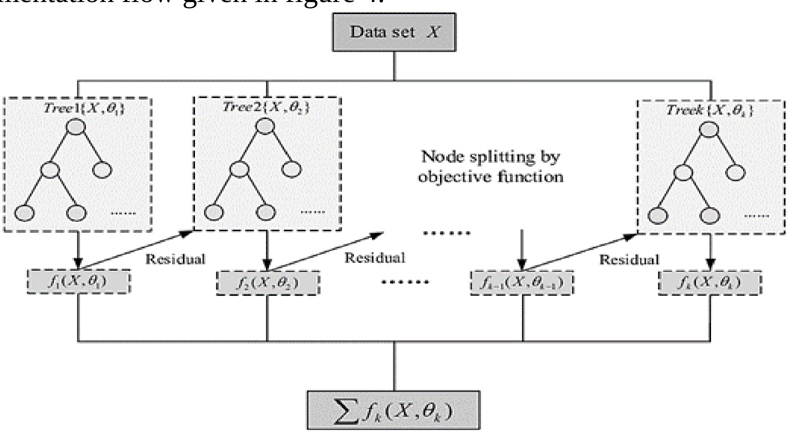

Fig. 4. Implementation flow of XG Boost

Given a labeled dataset $Q_{D,}$

$$Q_D = \{(f1,t1),(f2,t2),\ldots,(fn,tn)\}$$

Where, *fi* denotes to the feature vector of the *i*-th sample, *ti* denotes to the label that corresponds to the classification

Define hyperparameters for training, for each iteration *k* from 1 to *ntrees:*

Calculate the residuals or pseudo-residuals $ri^{(k)}$ of the predictions from the previous iteration:

$$r_i^{(k)} = y_i - \hat{y}_i^{(k-1)}$$

Build a new decision tree *Tk* to predict the residuals $ri^{(k)}$, then update the model's predictions using the new tree:

$$\hat{y}_i^{(k)} = \hat{y}_i^{(k-1)} + \eta \cdot T_k(x_i)$$

Finally, use the ensemble of trees to make predictions for new data.

$$\hat{y}_{\text{new}} = \hat{y}_{\text{new}}^{(0)} + \eta \cdot \sum_{k=1}^{n_{\text{trees}}} T_k(x_{\text{new}})$$

Algorithm 5: Implementation of XG Boost

Step 1: Initialization - Start with a base model prediction.
Step 2: Set Hyperparameters - Define learning rate, number of trees, depth, subsampling ratios, and regularization parameters.
Step 3: Iterative Training:

Compute residuals for the current model.

Fit a new tree to predict these residuals.

Update the model with the new tree's predictions.

Apply regularization to control overfitting.

Step 4: Handle Missing Values: Automatically handle missing data during tree construction.
Step 5: Model Prediction: Aggregate predictions from all trees in the ensemble.
Step 6: Model Evaluation: Assess model performance using relevant metrics.
Step 7: Hyperparameter Tuning: Fine-tune model parameters to enhance performance.

4.Experimental Results and Discussion

4.1 Experimental Setup

The primary objective is to predict using the model's conserved input variables to forecast the level of performance of a student based on two benchmark datasets. The classification model was built using a variety of machine-learning approaches, and the individual performances of each strategy were assessed. The minimum system specifications necessitate 16 GB of Random Access Memory (RAM) and an Intel Core i5 Central Processing Unit (CPU). Additionally, the software bundles encompass the Anaconda Distribution and the Pycharm Integrated Development Environment. Python's Scikit Learn module allows for the implementation of several ML models. The performance of each classifier model is assessed by cross-validation, with 70-30% of the data used for train and test phase. Questionnaire Datasets are the typical benchmark datasets used in the proposed experiment. [15], and the real-time gathered dataset to evaluate the recommended prediction model.

4.2 Evaluation Parameters

The proposed experiments employed on two datasets consisting of questionnaires to check the efficacy of the prediction model. The accuracy of the classification model is assessed using the following metrics: Accuracy (Acc), Recall (Rec), Precision (Pre), and F1-measure (Fmea). One way to evaluate a prediction system's efficacy is to look at the ratio of successful predictions to total occurrences. The accuracy of a forecast is determined by its rate of correctness. Recall, a statistic, measures the ratio of accurately predicted instances inside a certain real-world category. The harmonic mean of recall and accuracy was shown using the F-measure that was calculated. The calculation of these four metrics is achieved by applying the following equation to the confusion matrix.

$$ACC = \frac{TP+TN}{P+N} = \frac{TP+TN}{TP+TN+FP++FN}$$

$$Recall = \frac{TP}{TP+FN}$$

$$Precision = \frac{TP}{TP+FP}$$

$$F = 2.\frac{precision.recall}{precision+recall}$$

Where TP – True instances that are Positive,
TN – True instances that are Negative,
FP – False instances that are Positive,
FN – False instances that are Negative.

4.3 Results Analysis

Both datasets was subjected to four categorization methods, resulting in a range of conclusions and further analysis. The cross-validation technique was employed to evaluate four machine learning classifiers for the best accuracy, and the evaluation results are presented in Tables 6 to 9 for dataset-1 and in Tables 10 to 13 for Dataset 2. Table 5 displays the runtimes of the prediction model's training and testing procedures. Compared to the rest of the classifiers, MLP classifiers need the largest proportion of training time for both datasets as shown in Figure 5 since they have more hyperparameters for tuning.

Table 5. Assessment Time of Model

Classifiers/ Parameters	**Train Time (sec)**		**Test Time (sec)**	
	Dataset-1	**Dataset-2**	**Dataset-1**	**Dataset-2**
MLP-NN	54.7	55.8	25.4	26.5
RF	42.8	43.1	18.3	19.2
SVM	45.2	46.4	21.5	22.1
XGB	47.1	48.5	22.8	23.4

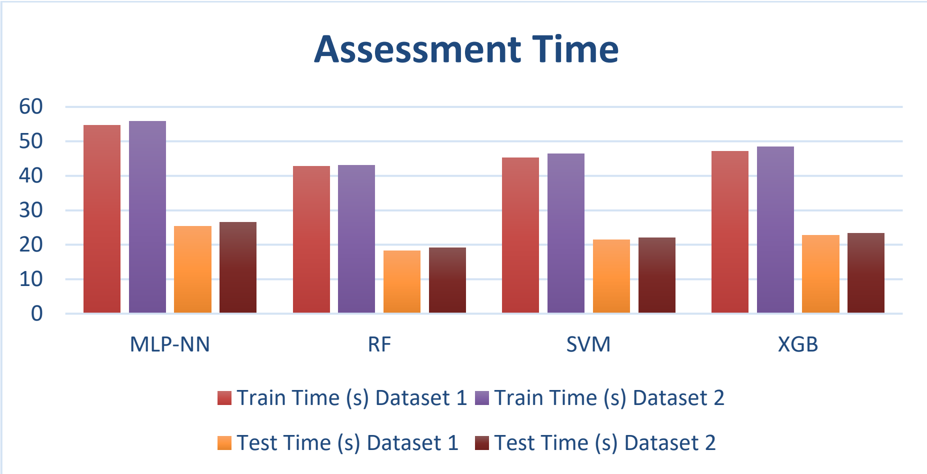

Fig. 5. The assessment time of the prediction model

While evaluating for dataset-1, the results produced by the RF classifier outperform those of MLP and other classifier models. It gets 90.0% of the classes correctly, which means that out of the four potential classes in the testing dataset, most students were placed in one of the other three. Overall recall, precision, and f-measure values for the testing model were 0.92, 0.88, and 0.88 for class-1 output respectively, indicating stable predictive performance. The outcomes show that RF outperforms the other models we tested for the prediction model. To further assure our prediction model, a further test was conducted using RF only on the testing dataset; this yielded better results than MLP-NN.

Table 6. Performance Evaluation of MLP-NN Model based on Dataset-1

Parameters/ GPA	**Class1**	**Class2**	**Class3**	**Class4**
Rec	0.81	0.59	0.53	0.67
Pre	0.85	0.65	0.61	0.74
F1-mea	0.72	0.67	0.57	0.70

Table 7. Performance Evaluation of RF Model based on Dataset-1

Parameters/ GPA	**Class1**	**Class2**	**Class3**	**Class4**
Rec	0.92	0.64	0.65	0.78
Pre	0.88	0.69	0.67	0.78
F1-mea	0.88	0.67	0.60	0.78

Table 8. Performance Evaluation of SVM Model based on Dataset-1

Parameters/ GPA	**Class1**	**Class2**	**Class3**	**Class4**
Rec	0.81	0.50	0.40	0.50
Pre	0.67	0.45	0.47	0.57
F1-mea	0.73	0.47	0.43	0.53

Table 9. Performance Evaluation of XGB Model based on Dataset-1

Parameters/ GPA	**Class1**	**Class2**	**Class3**	**Class4**
Rec	0.81	0.56	0.58	0.65
Pre	0.79	0.58	0.63	0.70
F1	0.80	0.57	0.55	0.77

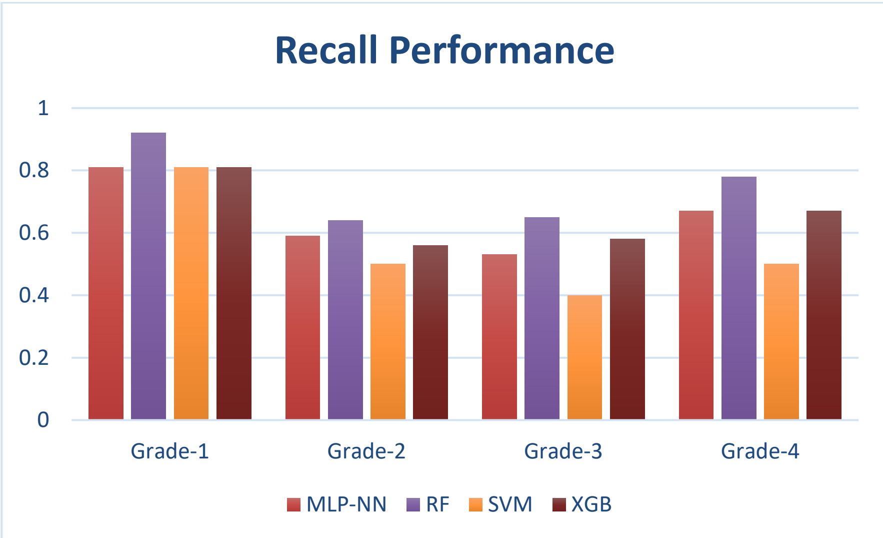

Fig. 6. Prediction Model Performance Using Recall on Dataset-1

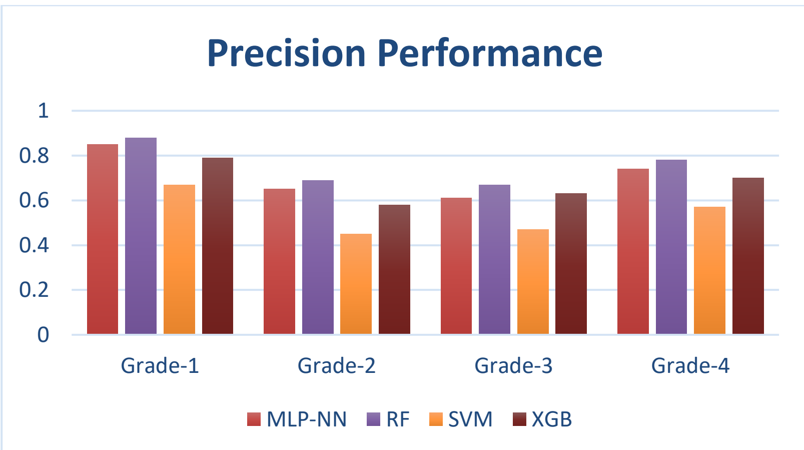

Fig. 7. Prediction Model Performance Using Precision on Dataset-1

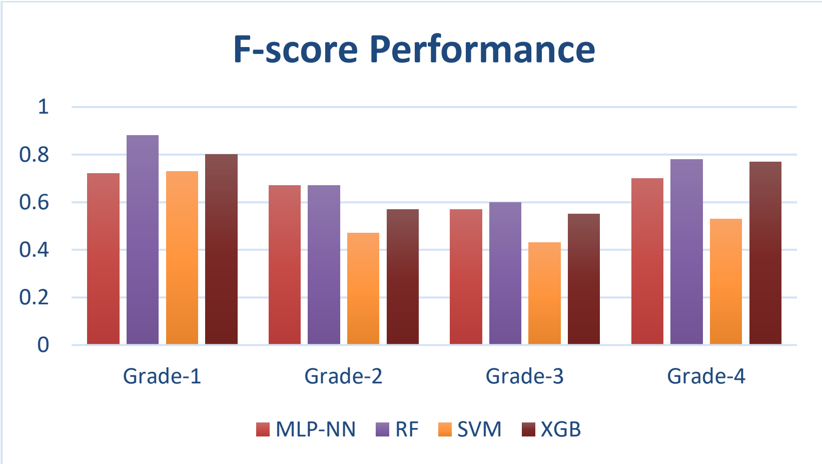

Fig. 8. Prediction Model Performance Using F-score on Dataset-1

During the analysis of dataset 2, in comparison to the MLP and other classifier models, the RF classifier excels in performance. The model achieved an accuracy rate of 93.0%, accurately classifying the majority of the classes in the testing dataset. This indicates that most students were assigned to one of the three alternative courses, out of the four possible classes. The testing model demonstrated steady predictive performance for class-1 output, with recall, accuracy, and f-measure values of 0.95, 0.91, and 0.91 respectively. The findings show that RF has higher prediction accuracy than the other models. To enhance the reliability of our prediction model, we ran an additional test utilizing the Random Forest (RF) algorithm only on the testing dataset. This test produced superior results compared to MLP-NN.

Table 10. Performance Evaluation of MLP-NN Model based on Dataset-2

Parameters/ GPA	Grade-1	Grade -2	Grade -3	Grade -4
Rec	0.84	0.63	0.57	0.71
Pre	0.89	0.69	0.65	0.78
F1-mea	0.76	0.71	0.61	0.74

Table 11. Performance Evaluation of RF Model based on Dataset-2

Parameters/ GPA	Grade-1	Grade-2	Grade-3	Grade-4
Rec	0.95	0.67	0.68	0.81
Pre	0.91	0.72	0.70	0.81
F1-mea	0.91	0.70	0.63	0.81

Table 12. Performance Evaluation of SVM Model based on Dataset-2

Parameters/ GPA	Grade-1	Grade-2	Grade-3	Grade-4
Rec	0.84	0.52	0.43	0.53
Pre	0.70	0.48	0.50	0.60
F1-mea	0.76	0.50	0.46	0.56

Table 13. Performance Evaluation of XGB Model based on Dataset-2

Parameters/ GPA	Grade-1	Grade-2	Grade-3	Grade-4
Rec	0.85	0.60	0.62	0.69
Pre	0.83	0.62	0.67	0.74
F1-mea	0.84	0.62	0.59	0.81

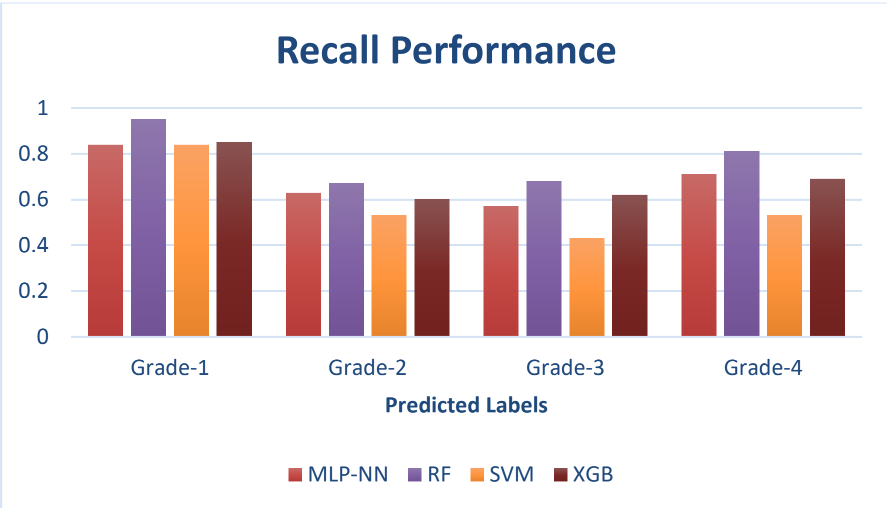

Fig. 9. Prediction Model Performance Using Recall on Dataset-2

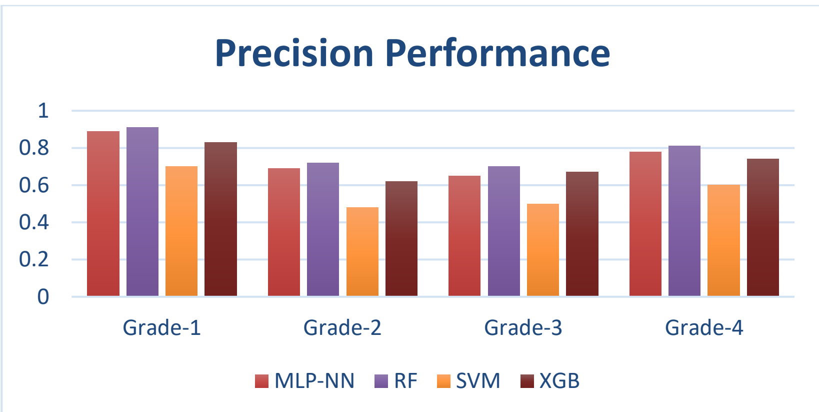

Fig. 10. Prediction Model Performance Using Precision on Dataset-2

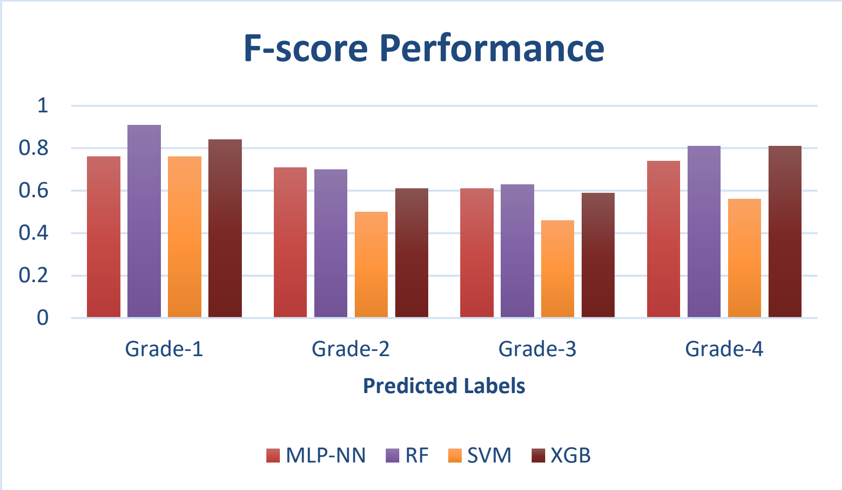

Fig. 11. Prediction Model Performance Using F-score on Dataset-2

The factors that impacted the value of our focal variable (CGPA) are also studied. Students' cumulative grade point averages were negatively impacted by their usage of online resources for instruction during the lockdown, according to its results. Overall grade point average was inversely related to the positive Likert scale ratings of these factors. The harmful impact of students spending too much time on digital tools on their academic achievement was confirmed once again. Low cumulative grade point averages were also more common among students who blamed their e-learning tasks for their excessive home-schooling. The most negative association was found between the student's final score and distractions from the digital instruments utilized for the online study. The main findings align with the research that shows a substantial impact of COVID-19 on children's academic performance.

4.4 Comparative Analysis

The statistical parameter, F-measure of 76.55%, a recall of 77.8%, a precision value of 78.6%, and an accuracy of 87.1% are all shown in Table 14, which illustrates the outcomes of our model. This proves that our model's prediction is accurate. Figure 12 depicts the absence of overfitting from the train-to-test dataset, which is evident from the balanced recall and accuracy performance using RF classifier algorithms.

Table 14. State of Art Model Comparative Analysis

Parameters/ References	**Ref [14]**	**Ref [18]**	**Ref [24]**	**Proposed Model**
Accuracy (%)	63.51	76.19	68.7	87.1
Recall (%)	63.5	52.70	68.9	76.8
Precision (%)	59.4	66.10	69.1	78.6
F-score (%)	61.4	58.64	67.8	76.5

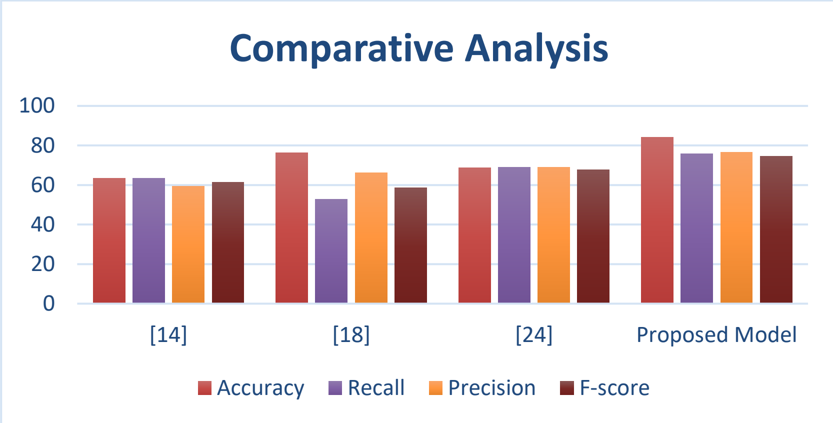

Fig. 12. Comparison with state-of-art Model

5. Conclusion

The rapid shift to e-learning during the COVID-19 pandemic highlighted significant challenges in monitoring and supporting student academic performance in e-learning environments. This paper addressed these challenges by leveraging supervised machine learning models to predict student outcomes based on data such as student demographics, use of e-learning tools, sleeping habits, psychological state, and academic scores. All these data collected on the effects of the lockdown on student's mental health and academic performance as well as their use of internet resources. Multiple models, including MLP-NN, RF, SVM, and XG-Boost were evaluated, with RF achieving the highest accuracy of 87.1%, demonstrating its robustness in handling complex and multi-dimensional educational datasets. The results underline the importance of data-driven approaches in identifying at-risk students and enabling timely interventions to support their academic success.

Furthermore, this paper highlights the adaptability of machine learning in addressing the unique challenges posed by e-learning, offering valuable insights for educators and institutions to develop more personalized and responsive education systems. While the findings are promising, future work should focus on integrating diverse datasets, addressing data privacy concerns, and exploring the applicability of deep learning models for enhanced predictions. Future research should focus on integrating broader, multimodal datasets, including behavioral and psychometric data, to improve model performance and robustness. Exploring advanced techniques such as deep learning and hybrid models could also enhance predictive accuracy.

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